Development of Decision Support System for Rescue Operations during Floods using Social Networks, Mobile Positioning Data and Aerial Imagery

A SYNOPSIS

Submitted by

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CHAPTER 1: AREA/SPECIALIZATION OF PROPOSED RESEARCH WORK

Computer Science & Engineering / A system technological approach using deep learning, Geographical information system, thermal imagery, mobile positioning data, and social media.

CHAPTER 2: TITLE OF PROPOSED RESEARCH WORK

Development of Decision Support System for Rescue Operations during Floods using Social Networks, Mobile Positioning Data, and Aerial Imagery.

CHAPTER 3: INTRODUCTION

Flood is one of the major disasters around the world. India is one of the most affected countries by floods. Flood disasters impact lives on a massive scale by harming many human lives, animals, physical assets, facilities. It creates local environmental disturbances and affects the livelihoods severely. Government, non-governmental organizations (NGOs), and local bodies do their utmost to rescue and save people's lives and assets from devastation. Specific to India, two central government agencies, namely the National Disaster Response Force (NDRF) and the National Disaster Management Authority (NDMA), are mainly vested with the task of the management and actions during disasters at the national level. Many other national, state-level and local bodies are also involved in disaster management activities.

There is a plan to develop a novel and useful technological model for rescue operations using social media, deep learning, mobile positioning data, GIS, drone, thermal imaging, and aerial imaging by utilizing modern concepts, techniques & technologies. It creates an integrated solution to make operations easy at the time of rescue. This synopsis explains how a well-defined technology model can play an effective role in the response and recovery phase of a flood disaster. At the flood response phase, relief agencies want to know where flood victims are located, what things are required to them, and who is in a safe zone. This information is often hard to get through conventional data mining techniques. In this present model, data mining in each module will be appropriately extracted, stored, managed, analyzed, executed, and adequately notified with better methods.

The need for a dedicated integrated decision support system with integration of all technical sections for the flood was felt after studying the work of many researchers in the literature. This synopsis addresses both the flood scenarios mentioned below.

- Connected Workflow: In this scenario, it is assumed that the flood has arrived, but the basic amenities like electricity and the internet network is still operational. In other words, flood victims can even communicate with the outer world. They are moving to

some safer places, either managed by the government or on their own. In this case, social media and mobile positioning data are considered as a vital source of information.

Disconnected Workflow: In this scenario, it is assumed that the local infrastructure is wholly damaged and vanished. There is no web or system through which flood victims can interface with the external world. Many people are stuck somewhere or missing. It means flood has damaged all connections to reach out to an affected person. In this case, Aerial Imaging, deep learning techniques, are considered as essential inputs for the process workflow.

CHAPTER 4: OBJECTIVE

Below are the research objectives and scope of Ph.D. research work.

- Extracting relevant data from social networks, processing, and create notifications for rescue operations.
- Extracting MPD from MNO’s and identifying the flood survivor’s position for their immediate help during rescue operations.
- Extracting drone video/Image data and then identifying survivors from the video/image using the 'Deep Learning' technique. Extracting drone thermal maps through geothermal infrared cameras and applying 'Deep learning' algorithms to identity humans in flood rescue operations.
- Integration of different data feeds.
- Designing and developing the architecture of a decision support system during flood rescue operations.

CHAPTER 5: HYPOTHESIS

It is observed from previous works and studies that still, there are many challenges while developing an integrated system where it can adopt innovative works for rescue operations and finally integrate the components. Also, it should be accessible to the concerned service, department, or person. It is felt that still there is a vast scope of utilizing the capabilities of Social media data, Mobile Positioning Data, and Deep learning on aerial imaging in a better way. This work will address a better and integrated approach using the best available technology, ideas, algorithms, and innovations.

3.1.1 Processing social media data for rescue operations:

Other studies in the past explain either a partial or primitive approach to store & process the Twitter data. Rescue agencies are still finding better ways to store and process massive amounts of social media and other valuable data. GIS-based analysis in social media data is minimal. Data mining at street level is limited to locate the exact location. No. of Camps, No. of Victims families, Total Inmates, House Partially Damage, House Fully Damage, Injuries, Missing, and Deaths is limited and needs more explorations and victims engagements to ensure transparency. The geocode issue is not addressed in flood management. The geo-tagging photo which clicking pictures and sending photos on twitter is limited.

The present study will develop the complete life-cycle, right from the twitter extraction to the creation of 'location events' and sending it to appropriate government authority for the next course of action. Latent Dirichlet Allocation (LDA), Doc2Vec, and K-means algorithms will be used to cluster the twitter data in different groups. Advanced technological systems like big data will be used to store, geo-analyze, and report huge spatial and non-spatial data for better performance. Various important parameters will be considered, like No. of Camps, No. of Victims families, Total Inmates, House Partially Damage, House Fully Damage, Injuries, Missing, and Deaths to create 'location events.' In the current approach, geocoding and geo-tagging methods are suggested.

3.1.2 Develop techniques of Mobile Positioning Data extraction, aggregation, and analysis:

In the past decade, much research had alignment on mobile position data either by any mobile application or mobile GPS data with a mandatory requirement of putting Mobile GPS ‘on.' At the time of the disaster, it looks impractical that people will use their mobile with location 'on' continuously throughout day and night daily during flood disaster. The battery gets consumed a lot when GPS is on. In earlier approaches, there is less work done on the development of live Current Population Density Diagram, People Movement Diagram, Safety Check Diagram, and Battery Charging Diagrams.

The current approach will utilize a better use of Mobile Positioning Data (MPD) data in flood disasters during rescue operations and develop crisis tools. Complete life-cycle will be established, right from extracting MPD from MNO’s to identifying the flood survivor’s position for their immediate help during rescue operations. In this study, the following questions will be addressed: the cellular network has been damaged in which area? Where would flood victims be able to get to a mobile network to associate with their family & friends? Where are people prepared to charge their mobile in a disaster-impacted region? What does this deduce about electricity accessibility? After and during a disaster, how many people dislodged from their home towns? From which cities these individuals are displaced? Moreover, those individuals are moving to which town? All results and diagrams like Population Density Diagram, Movement Diagram, Safety Check Diagram, and Battery Charging Diagram came out after adopting various data aggregation analytics on mobile positioning data.

3.1.3 Creation of data models in Deep learning for object detection on Aerial Imaging:

In past investigations, much research has been developed on search & rescue operations using a drone in an open sky and amid daylight time only. There are minimal findings where the human rescue team can work in an adverse situation like fog, complete night, rain, and partial vegetations. Capturing, Merging, and tiling of drone aerial images is also a challenge. Storing and analyzing these enormous sizes of videos and images is also a big challenge. Finding tiny/partial human pattern in videos and images are also limited.

In this present work, a model will be developed through which the rescue team can work day and night during search and rescue operations. This model will be designed to work also in unfavorable environmental conditions such as rain, mist, complete darkness, partial vegetations and sun-rays blinding, etc. The objective of this investigation is to get better outcomes when a drone flies with thermal cameras in hazardous flood regions during rescue activities and then imitate the deep learning thermal models with Aerial and thermal Imaging data to locate the living objects that are lying, stuck, hide, or moving in some areas. This study will be tasked to identify moving, abandoned, or partially visible human patterns in a recording or an image captured by a flying drone in the influenced zone through pattern recognition methods & produces high-resolution technical output.

3.1.4 Integration of techniques and the development of DSS for flood rescue operations:

In earlier approaches, DSS is made, but there is a gap in communication. It was challenging to get a communication platform where rescue team members can communicate, create, and allocate tasks. Sharing of video, text, and image data is also minimal when they are into the field and offline. All technological initiatives are not integrated.

In this present work, A new approach will be developed, which will address the integration of different data feeds of Social media, Mobile positioning data, and thermal imaging. It also develops Designing and developing the architecture of a decision support system during flood rescue operations. The final results of social media, mobile positioning Data, and deep thermal imaging components will be integrated to create an integrated decision support system. It will combine all the solutions components into one platform in such a way that one module can take all the inputs from other data sources hassle-free. For example, compiled and live social media and mobile positioning should be readily available to the drone or rescue team as “location events." Rescue center team will processes these “location events” into “action events” after getting MPD data and thermal imaging data so that they could plan their flight operations or any other actionable instant measures in the affected area.

CHAPTER 6: LITERATURE REVIEW

6.1 Processing social media data for rescue operations:

6.1.1 Review of related work:

B. Klein et al., 2012[15] utilize social network analysis to distinguish solid tweets and content investigation systems to condense key crisis actualities by separating unstructured and uproarious nature of tweets. **F. Cheong & C. Cheong, 2013[11]** distinguish a scope of fundamental resources during the Queensland flood, for example, local agencies (mostly the Queensland Police Services), political characters (Queensland Premier, Prime Minister, Opposition Leader, Member of Parliament), social media participants, customary media correspondents, and individuals from non-revenue agencies, compassionate, and network affiliations. **T. Funayama, Y. Yamamoto et al., 2014[2]** developed a framework to separate catastrophe data and dissect Tweet on Twitter by utilizing API (Application Programming Interface).**Z. Ashktorab, C. Brown, et al., 2014[1]** presented Tweedr, a pipeline comprises of three primary parts: order, grouping, and extraction. In the order stage, they utilized an assortment of grouping strategies to recognize tweets announcing harm or losses. **P.M. Landwehr & K.M. Carley, 2014[18]** recommend another product platform to decipher the approaching information from social media in a superior manner, just as to send innovations explicitly to reap messages from fiasco circumstances. **A.A. Khaleq, 2014[7]** suggests a cloud-based framework system centered with respect to three principle parts of fiasco significance characterization, calamity stage arrangement, and information extraction. **R. Power et al., 2014[19]** make one Emergency Situation Awareness (ESA) structure, which assembles enormous volumes of Twitter data and recognizes exchange strings, designs, and fervently discussed issues using language models.

A. Attanasio et al., 2015[12] propose a stage to comprehend the fundamental concerns given by users and gauge the effects of various alternative activities that can be attempted by management people. **M. Yadav & Z. Rahman, 2016[9**] suggest**s** a better understanding of the role social media can play in natural disaster resilience in the Indian context. **P. Gunawong & N.**

Butakhieo, 2016[4] give a comprehension of how the Bangkok Metropolitan Administration (BMA) in Thailand has embraced Twitter to speak with occupants in its way to deal with the flood. The percentage of contacted people was less as compared to the total affected people. The study explains BMA was successful in identifying the merged area on a high level. **B. Anbalagan & C. Valliyammai, 2016[6]** performs Naive-Bayesian (multinomial) and SSVM (Smooth Support Vector Machine) categorization on gathered tweets to recognize the seriousness of the catastrophe. **J. Yeo et al., 2016[10]** observe flood response communication had strong cultural characteristics on Twitter. **R. I. Ogie & H. Forehead, 2017[3]** investigate to enhance comprehension of the degree to which geo-referenced area of flood reports in Social media stray from the real areas of floods **O. Ozdikis et al., 2017[16]** gauge the location of occasions concerning the targeted event type, the granularity of evaluated location, location related highlights chose as a source of spatial proof. **J.P. Singh et al., 2017[17]** foresee user location of high need tweets with no location data dependent on recorded areas of the users utilizing the Markov model.

A. K. Layek, A. Pal, et al., 2018[5] clarify a technique for definition of the pictures posted on social networking sites, which lies on 'near-duplicate picture detection' to group the pictures.
K. Tzavella, et al., 2018[8] have built up an availability indicator to compute their crisis reaction reaches and crisis reaction paths through overflowed street systems with the assistance of geo-location and Tweeter data given by the refugee community. **L. John et al., 2018[20]** recognize the elements influencing coordination during catastrophe between different on-screen characters with the utilization of a hybrid fuzzy. **D. Giri & A. Vats, 2019[13]** feature the favorable circumstances and inconveniences of utilizing social media in debacle circumstances and make sense of the degree and confinements that can be a potential danger to social media's extensive use with respect to calamity management in India. **S. Muppidi et al., 2019[14]** characterize the cataclysmic event-based tweets from the users utilizing classification machine calculations like Naïve Bayes, Logistic Regression, k-nearest neighbors (KNN), Random forest and decide the best AI calculation (in light of measurements like exactness, kappa and so on).

6.2 Develop techniques of Mobile Positioning Data extraction, aggregation, and analysis:

6.2.1 Review of related work:

C. Takenga, C. Xi, et al., 2006[21] explains a hybrid NN (Neural Network) - information base relationship strategy (Database Correlation-DC). The DC position estimates are post-prepared utilizing an extra NN to diminish its error and to get the position of the people in the affected area. **R. Ahas et al.,2006[40]** present a synopsis of transient development examples and action spaces, particularly for examining travel journals, day by day action spaces, and space utilization, which is a basic issue in economical arranging of the sprawling urban areas. **R. Ahas, A. Aasa, et al., 2007[22]** also describe MPD, which enables one to connect the computerized track of tourists with visited proceedings & locations retrospectively. **O. Järv et al., 2007[41]** affirms the tremendous capability of the passive positioning method for considering visitors' space-time conduct at nearby goals. **R. Ahas & A. Aasa, 2008[32]** portray mobile positioning data, which has points of interest: information can be gathered for bigger spatial units and in less-visited times; spatial and transient exactness is higher than for the travel industry standard. **R. Ahas et al., 2008[33]** created an online travel management and monitoring framework: "Positium Barometer." Barometer utilizes passive mobile positioning data, which is another and promising hotspot for examining the topography of the travel industry and space-time conduct since the information is spatially more exact than some other information source. **R. Ahas et al., 2009[36]** utilize Passive Mobile Positioning Data to decide respondents' home and work anchor point locations. Built-up the model and tried it with a year's information gathered by Estonia's biggest mobile specialist organization, EMT, covering more than five lakhs mysterious respondents. **R. Ahas et al., 2010[31]** built up the model and tried it with a year's information gathered by EMT, Estonia's biggest mobile specialist organization, covering more than five lakhs mysterious respondents. Results were contrasted with populace register information; this uncovered the created model depicted the topography of the populace generally well.

R. Ahas et al., 2011[34] record the Location and timing of call exercises in network cells for each roaming mobile phone. Each mobile phone is depicted by its pseudonymous identification

and nation of a starting point. Results demonstrate that portability information assortment is more savvy than with past information assortment strategies. **W. Kellens et al., 2012[28]** led a contextual analysis on the Belgian coast, and both the dynamic idea of waterfront travel industry and the conduct of residential sightseers in storm flood situations are considered. Results show that including the travel industry elements for flood risk management is legitimized and suitable. **JJ. Figueiras, J. GrønbæK, et al., 2012[23]** propose and analyze a data fusion solution based on low-cost mobile, global positioning system (GPS) receivers joined with digital fences deliberately put at neighboring borders between sheltered and risky geographic regions. **X. Li, et al., 2012[29]** propose an improved Autoregressive Integrated Moving Average (ARIMA) based expectation strategy to gauge the spatial-transient variety of travelers in a hotspot. Assessment with an enormous scale genuine informational collection of 4 000 taxicabs' GPS follows more than one year. **R. Ahas, J. Armoogum, et al., 2014[24]** conclude that at present mobile positioning data can be used as an additional valuable input rather than a substitute source of data for the current official tourism indicators required. **ML. Lamp et al., 2014[27]** draw out methodological exercises on utilizing Call Detail Record based datasets as a hotspot for the travel industry insights and crisis management. It quantifies the effect of road riots and a political showdown on incoming tourism with the contextual investigation of the Bronze Night riots in Estonia, in April 2007.

K. Nilbe et al., 2014[39] analyzes whether the separations went by outside guests to occasions contrast from those went by non-occasion (i.e., normal) guests, and which elements impact such separations. **T. Vajakas et al., 2015[42]** propose a procedure for improving the precision of cell phone movement utilizing passive mobile positioning data when contrasted with ping-pong' concealment calculations. **Y. Setiadi & A. Uluwiyah, 2017[25]** examine how to improve the nature of survey output through Big Data with contextual investigations of MPD end-users in Indonesian Tourism Statistics**. Y. Setiadi & A. Uluwiyah, 2017[37]** talk about further how to improve the quality of survey data through Big Data with contextual analyses of MPD users in Indonesian Tourism Statistics. **P. Kamenjuk et al.,2017[38]** presents a system for mapping changes of the home utilizing information from passive mobile positioning and an anchor point model for the investigation of the associations between day by day portability and change of home. **R. Toujani et al., 2018[30]** decide critical cases and to concentrate on immersive

sentiment analysis for large social information utilizing the Hadoop and AI procedure and apply support vector machine calculations for the opinion grouping. **Z. Pang et al., 2018[43]** present an examination of whether and how the mobile-internet positioning data can profit-building vitality reproduction. Results show that mobile-internet positioning data can help improve the structure model forecast precision. **P. Maas, L. McGorman, et al., 2019[26]** develops new tools for disaster management based upon one mobile application and GPS data. **W.O.Z. Madjida, 2019[35]** clarifies how the Mobile Positioning Data (MPD) can advance a superior answer for convenience insights. Mobile Positioning Data (MPD) can be utilized to screen individuals' development and remains in the watched zone

6.3 Creation of data models in Deep learning for object detection on Aerial Imaging:

6.3.1 Review of related work:

J. Davis & V. Sharma, 2004[93] present another shape-based foundation subtraction procedure to identify individuals in generally varying thermal imagery. They show the power of the way to deal with identify individuals over a wide range of thermal imagery utilizing a fixed arrangement of parameters. **S. Mandal, D. Saha, et al., 2005[51]** proposed a flood estimating method that depends on an artificial neural system (ANN) model, specifically, multi-layer perceptron (MLP). **P. Doherty & P. Rudol, 2007[56]** offer how far they have come in executing testing missions where UAVs filter assigned territories and attempt to recognize injured people. Additionally, an endeavor is made to convey restorative and different supplies to distinguished unfortunate casualties through UAV. **P. Rudol & P. Doherty, 2008[79]** present a system that permits recognizing people at a high frame rate on standard equipment interface of a self-sufficient UAV in an outside condition utilizing thermal and color imagery. It very well may be utilized to design medicinal inventory conveyance during a catastrophe aid project**. H. Sheng et al., 2010[89]** presented ease UAV-based TIR (Thermal Infrared) remote detecting stage: AggieAir-TIR. A modest TIR imaging camera adjustment analyzes structured, and the alignment results are given. **Y. Chen et al., 2011[62]** present computer vision-based horizon detection and target following for the recordings caught by UAV camera. The proposed skyline discovery calculation is an upgrade of Cornell's Theorem, and its objective following utilizes the optical stream.

A. Gaszczak et al., 2011[91] present a methodology for the programmed location of vehicles dependent on utilizing different prepared cascaded Haar classifiers with secondary affirmation in thermal imagery. **J. Lu et al., 2011[69]** structured the essential location strategy and improved recognition technique is moving items discovery module, which viably coordinates the customary single-outline identification innovation and multi-outline identification innovation into our system. **A. M. Jensen et al., 2012[94]** present a stage for ease, high-resolution thermal imagery utilizing an unmanned flying vehicle (AggieAir 1) **A.F.M.S. Saif et al.,2013[60]** present an applied structure for moving item discovery with moving the camera from UAV airborne pictures joined with the casing contrast and division approach together.

X. Tong et al., 2013[70] propose a framework which incorporates: (1) an element grouping based various objects following structure which performs superior to the conventional frontal area mass following based strategies. (2)Optical stream highlights are bunched both in spatial and fleeting measurements to follow various items heartily even on account of various objects cross moving. **M. Vasterling & U. Meyer, 2013[83]** location the identification of the irregularities in ground surface temperature actuated by consuming underground coal. They portray the difficulties and chances of UAV-borne thermal imaging in light of our encounters in the field. **J. Portmann, S. Lynen, et al., 2014[74]** introduces another, the freely accessible dataset of annotated thermal picture successions, representing a large number of difficulties for an individual's location and tracking. Additionally, they propose another particle filter based structure for searching individuals in thermal aerial pictures. **J. Portmann et al., 2014[82]** present another, a freely accessible dataset of annotated thermal image sequences, representing a huge number of difficulties for individuals discovery and following. It proposes another particle filter-based system for following individuals in elevated warm pictures. **M. Teutsch et al.,2014[85]** propose a two-stage individual identification approach for LWIR pictures: (1) the utilization of Maximally Stable Extremal Regions (MSER) to recognize problem areas rather than foundation subtraction or sliding window and (2) the confirmation of the distinguished problem areas utilizing a Discrete Cosine Transform (DCT) based descriptor and an adjusted Random Naïve Bayes (RNB) classifier.

R. Gade & T.B. Moeslund, 2014[97] give a review of the present utilizations of thermal cameras. Applications incorporate creatures, farming, structures, gas detection, mechanical, and military applications, as well as searching, tracking, and identification of people. **A.S. Vempati et al., 2015[58]** give a pipeline to productively combine thermal and visual elevated imageries for strong continuous discoveries. Identifications are followed crosswise over different casings, and the ongoing GPS locations of the unfortunate casualties are passed on. **R. Strydom et al., 2015[59]** present a stereo-based strategy for the capture attempt of a static or moving objective, from an Unmanned Aerial Vehicle (UAV). A Kalman filter figures a reliable gauge of relative position and speed utilizing the target centroid. **T. Giitsidis et al., 2015[87]** recommends to take shadows, movement recognition, and object tracking can be utilized to delineate people. Parallel picture preparing is being worked upon with the assistance of a specific equipment gadget dependent on Field Programmable Gate Array (FPGA)

F. S. Leira et al.,2015[96] Incorporate the machine vision framework for the utilization of a thermal imaging camera and locally available preparing capacity to perform constant object discovery, grouping, and following of object in the sea surface. **S. Sharma, 2016[73]** proposes a two-stage approach for human search in LWIR (Long-Wavelength Infrared) pictures: (1) the usage of MSER (Maximally Stable Extremal Regions) to perceive problem areas instead of foundation subtraction or sliding window and (2) the approval of the recognized problem areas using Integral Channel Features (ICF) and a Naive Bayes classifier. As a general rule, different ecological conditions influence seriously to the yield produced by UAVs. **G. Häger et al., 2016[68]** propose a combination between an online tracker and a pre-prepared finder for following people from a UAV. Additionally, they present a novel dataset for long term following in a UAV setting that incorporates situations that are commonly not all around spoke to in standard visual following datasets. **J. Redmon, S. Divvala, et al., 2016[71]** present You Only Look Once (YOLO), which is another way to deal with entity recognition. Earlier work on item recognition repurposes classifiers to perform detection. Later, **J. Redmon & A. Farhadi, 2016[72]** present YOLO9000, a best in class, ongoing object detection framework that can identify more than 9000 item classifications. The study proposes different upgrades to the YOLO recognition strategy, both novel and drawn from earlier work. **K. He, X. Zhang, et al., 2016[53]** explains that it is increasingly difficult to prepare deeper neural systems. They address training

residual functions to make it easier to plan structures that are significantly deeper than those already used. **Y. Ma et al., 2016[80]** concentrates passerby masses utilizing the local slope highlight and geometric imperatives separating and afterward orders the distinguished masses by utilizing a direct Support Vector Machine (SVM) with a crossover descriptor, which adroitly joins Histogram of Oriented Gradient (HOG) and Discrete Cosine Transform (DCT) includes to accomplish precise recognition. This methodology utilizes the element tracker with the update of the recognized walker area to follow a person on foot objects from the enrolled recordings and concentrates the movement direction information. **J. Kümmerle et al., 2016[63]** propose an ongoing framework to recognize and follow numerous people from high bird's-eye sees by web-based learning of an objectness model which is utilized for refreshing a Kalman channel.

E. Levin et al., 2016[90] indicate the feasibility of using Small Unmanned Aerial Vehicles (SUAV's) and small thermal sensors for the human detection scenarios. Electro-optical imagery was used for research in optimal human detection algorithms. **M. Krišto, 2016[92]** present techniques on the utilization of thermal imaging frameworks for human discovery, acknowledgment, and recognizable proof. Likewise, it depicts procedures and strategies for face recognition and human identification dependent on the thermal picture (thermogram). **A. Maher et al.,2017[67]** propose an ongoing human motion identification for controlling a smaller scale UAV in a GPS denied condition by building up a Human-UAV Interaction (HUI) framework. **J. Witczuk et al., 2017[84]** consolidate unmanned flying vehicles (automatons) and thermal infrared (TIR) imaging as a device for ungulate overviews. **W. G. Aguilar et al., 2017[88]** propose a strategy dependent on HAAR-LBP (High Altitude Aerial Reconnaissance - Local Binary Patterns) course classifiers with Adaboost (Adaptive Boosting) preparing, and they consolidate course classifiers with saliency maps for improving the performance of the pedestrian identifier. For the preparation dataset, pictures are caught from reconnaissance cameras at various points and heights.

J. Tao, H. Wang, et al., 2017[45] describes another object recognition technique, OYOLO (Optimized You Only Look Once), which is 1.18 times quicker w.r.t YOLO, thus beating other locale-based methodologies, for example, R-CNN. **E. Aribas & E. Daglarli, 2017[46]** explain the Yolo concept, which is viewed as a key component for real-time object recognition. **S. N.**

Longmore et al., 2017[95] adopted a multi-disciplinary strategy. They utilized unreservedly accessible astronomical source recognition programming and the related aptitude of astronomers, to productively and dependably distinguish people and creatures in aerial Thermal infrared film. **D. Cavaliere et al., 2018[57]** present an observation UAV-based framework, planned for understanding the scene circumstance by gathering crude information from nature (by exploiting some conceivable sensor modalities: CCTV camera, infrared camera, thermal camera, radar, and so on.), preparing their combination and yielding a semantic, significant level situation depiction. UAVs can perceive items and Spatio-worldly relations with different objects and the environment. **C.C. Andrea et al.,2018[61]** present a created framework dependent on the cooperative energy of a UAV, and geo-location calculation that identifies individuals with flying shots in territories of troublesome access and prepared to channel, separate, tally geo-restricted individuals in danger with the assistance of Artificial Neural Networks (ANN). **A. Woodward, 2018[54]** mentions, it is observed that enormous data resides nowadays w.r.t any other old times following any calamity because of unmanned aerial vehicles (UAVs) and advanced satellite systems that can catch live pictures of fiascos from the air. **C. Beleznai, D. Steininger, et al., 2018[75]** suggest a run-time-productive multi-modular identification modal performing grouping & detection on the thermal infrared, passive stereo depth & intensity channel to accomplish human recognition results. **M.M. Khan, 2018[77]** reports the development of a novel list of capabilities for arranging surfaces in low-resolution thermal infrared (TIR) pictures like the ones obtained amid airborne and ground activities of automated vehicles. **Y. Shao, Y. Mei, et al., 2018[78]** suggests a mob movement approximation framework dependent on the corner identification & different scale optical stream utilizing the upsides of working throughout the day of infrared cameras and high adaptability of the Unmanned Aerial Vehicle. This can make it faster to locate a person but more likely to miss them. The reverse is with a wide field of view that provides better clarity on the accuracy. However, it might be challenging to find the object as it looks similar to a thin soda straw. **I. Lahouli, Z. Chtourou, et al., 2018[76]** propose a quick and effective technique for the recognition of people in outside scenes utilizing thermal camera & taken images from flying stages. They begin by retrieving the shining blobs dependent on a combination between two things, that is a saliency map and a difference improvement method. **S. Xu, A. Savvaris, S. He, et al., 2018[47]** explains that visual entity recognition deep learning algorithm (YOLO) and Joint Probabilistic Data Association(JPDA) multiple target recognition

calculations were chosen and performed. After the arrangement, a significant learning machine can anticipate the event of quick questions in influenced regions of a debacle, utilizing a convolution neural system. **H. Jeong, K. Park, et al., 2018[44]** pictures a pre-treatment framework for images collected by a YOLO preparation crawler. YOLO is the third measure of object recognition in the YOLO family. With numerous traps, it enhanced the accuracy and is gradually fit to identify objects. **D. Avola et al., 2018[64]** present a vision-based framework to discover scrambled targets in obscure conditions by utilizing little scale robots and visual cryptography. This acquired momentous outcomes, and the proposed technique can be considered as a benchmark in the territory of the scrambled target pursuit by little robots.

D. Du et al., 2018[66] develop another UAV benchmark concentrating on complex situations with new level difficulties, chose from 10 hours crude recordings, around 80, 000 delegate outlines are thoroughly commented on with bouncing boxes just as up to 14 sorts of traits (e.g., climate condition, flying height, camera see, vehicle class, and impediment) **I. Lahouli et al.,2018[81]** propose a quick and productive strategy for the location of people in open-air scenes utilizing thermal pictures taken from airborne stages by extricating the bright blobs dependent on the combination between a saliency map and a complexity upgrade procedures. **N. Bhattarai et al.,2018[86]** proposes a framework for ongoing identification of people on recordings caught from UAVs tending to three of these requirements, in particular, flying tallness, calculation time, and scale of viewing. **M. Hong & R. Akerkar, 2019[55]** explored the utilization of AI systems to help the basic leadership forms for crisis management and talk about their difficulties, for example, situational awareness and real-time threat assessment utilizing differing surges of information. **P. Stodola et al., 2019[65]** presents the model of the Autonomous Aerial Reconnaissance Problem (AARP) The AARP can be viewed as an outstanding Multi-Depot Vehicle Routing Problem (MDVRP). The utilization of the model appears on the detachment level inside a picked strategic movement

6.4 Integration of techniques and the development of DSS for flood rescue operations:

6.4.1 Review of related work:

M.J. Booij, 2003[104] makes the hydrological, water-powered, and financial models inside the DSS, which are built reliably, considering the undertaking targets, qualities of the measures, spatial and fleeting scales and future situations. **S. Asghar et al., 2005[110]** showed the value of our model coordination by taking a theoretical calamity situation. The proposed method is made to get an incorporated model as an answer for lessening the multifaceted nature and wastefulness of managing different DSS models for calamity management. **Q. Yang & Q. Zhang, 2007[52]** describes the need and practicality of the crisis management, decision support framework of flood debacle. They also say that DSS advances the methodical system of overall procedure crisis management, & lastly, clarifies the capacity structure of each application subsystem. **Hu Zhuowei, Li Xiaojuan, et al., 2007[48]** describe that, with enhanced remote sensing and geological information systems, tracking and evaluation of flood hazards are being used to an ever-increasing degree. **I. A. D. Kort & M. J. Booij, 2007[109]** built up a procedure for the positioning of measures to help policymakers to make a vital determination between various principles in a DSS while considering uncertainty into account. **Y. Chen & X. Liu, 2008[50]** presents strategies for fast observing and assessing flood catastrophe based on RS and GIS technology. **D. Lumbroso et al., 2008[111]** portray the advancement of a general structure for DSSs for flood event management which ought to give the accompanying: a database of "pre-run" flood occasions; mapping of the flood peril; Location of the receptors in danger (for example individuals, structures, basic foundation); and subtleties of places of refuge and clearing courses.

HB. Du & L. Yu, 2009[100] built up three base models dependent on the hypothesis of an incorporated choice emotionally supportive network, in particular, the database, model base, and information base. **J. Tian et al., 2009[113]** proposed a system of choice decision supportive network in crisis reaction, which depends on the Hall for Workshop of Mate-manufactured Engineering through the procedures of Work Breakdown Structure (WBS). **M. Cioca & L.-I. Cioc, 2010[98]** portrays that to caution the populace if there should be an occurrence of fiascos in a consistently changing financial and social condition, associations, chiefs, experts and individuals in control, and so on must settle on fundamental choices brought about by the versatility of inside and external variables. **L. Fang, J. Yue, J. Dai, et al., 2010[49]** propose a

crisis reaction procedure dependent on debacle assessment models, and a flood crisis reaction framework is created. **M.H. Hsu et al., 2010[103]** built up a framework that incorporates the ongoing precipitation screen and gauge data, the peril potential, and the essential spatial database to help the crisis supervisors settling on choices effectively**. S. Shan et al., 2012[105]** propose a crisis reaction choice emotionally supportive network (ERDSS) on a system that comprises of ten useful modules: Problem Analysis and Management, Emergency Alarm Management, Emergency Knowledge Warehouse, Emergency Finance Budget Management, Emergency Relief Supplies Management, Emergency Plan Management, Command, and Coordination Center, and Emergency Service Helpdesk. **I. Tsekourakis et al., 2012[114]** give an intensive examination of existing evacuation models and systems, present the DSS engineering and installed calculations, and talk about its performance. **D. Alvear et al., 2013[112]** offer a decision support system (DSS) for crisis management in street tunnels. They utilize prescient devices to appraise the seriousness of the mishap or occurrence, just as rescue and evacuation times

L. Yaqoob et al., 2014[102] give a diagram of various fiasco management decision support system which is equipped for tending to a wide range of fiascos like a flood, tremor, dry spell, and so forth. **E.X. Sung et al., 2015[106]** built up a visual-based flood choice decision support system, called FloodViz to incorporate interdisciplinary information from meteorology and hydrology and give a reasonable depiction of the flood circumstance. **H. Mirfenderesk et al., 2016[101]** depicts the structure and the working model of a flood crisis decision support system as a proof of idea. It is in operation now and supports strategic and vital basic leadership during flooding on the Gold Coast. **S. Shan & Q. Yan, 2017[107]** depicts an emergency response decision support system (ERDSS) structure and its primary parts in detail. **P. D. Rajeshkumar et al., 2017[115]** clarify the Disaster Management Act, 2005, has given a constitution of National Disaster Response Force for a reaction to common and human-made debacles. NDRF is a framework of pro, prepared, taught, and committed faculty who can render help and reaction benefits in the best of the way in the most noticeably terrible of the circumstances. **R. Abdalla & M. Esmail, 2018[99]**, propose a computer-based framework for management leaders who manage semi-organized issues. **S. Saha et al., 2018[108]** built up an analytics dashboard for rescuer through which he will have more opportunity to be readied, and a superior arrangement will be delivered to protect the individuals and reallocate them into safe zones.

CHAPTER 7: RESEARCH METHODOLOGY

It is observed from previous works and studies that still, there are many challenges while developing an integrated system where it can adopt innovative works for rescue operations and finally integrate the components. Also, it should be accessible to the concerned service, department, or person. It is felt that still there is a vast scope of utilizing the capabilities of Social media data, Mobile Positioning Data, and Deep learning on aerial imaging in a better way. This work will address a better and integrated approach using the best available technology, ideas, algorithms, and innovations.

6.4.2 Processing social media data for rescue operations:

The following section gives the design of the concept and architecture in technical aspects of the framework that will be created aligned to the goal and motive.

6.4.3 Conceptual Architecture

The present study develops the complete life-cycle, right from the twitter extraction to the creation of 'location events' and sending it to appropriate government authority for the next course of action. Latent Dirichlet Allocation (LDA), Doc2Vec, and K-means algorithms will be used to cluster the twitter data in different groups. Advanced technological systems like big data are used to store, geo-analyze, and report huge spatial and non-spatial data for better performance. Various important parameters are considered like No. of Camps, No. of Victims families, Total Inmates, House Partially Damage, House Fully Damage, Injuries, Missing, and Deaths to create 'location events.' In the current approach, geocoding and geo-tagging methods are suggested

Twitter data can be stored in a Comma-Separated Values (CSV) file or to any Database Management System (DBMS) like *Hive* and *Postgres*. Movie Data, Twitter Batch & Twitter streaming are three important data APIs. In this study, through scripting of Python, this data could be retrieved and kept in the form of JSON (JavaScript Object Notation) & HDFS (*Hadoop*

Distributed File System) file formats. After doing analytics on the JSON data, the compiled data can be saved in PostgreSQL. *Microsoft BI or Tableau*, or any other analytical programming can be utilized to show the dashboard and report publishing part of the framework.

6.4.4 Develop techniques of Mobile Positioning Data extraction, aggregation, and analysis:

An analysis will be conducted by considering the research ' Feasibility Study on the Use of Mobile Positioning Data (MPD) for Tourism Statistics' as a study base and then adapting MPD to perform different flood-specific spatial analytics.

Four extraordinary knowledge diagrams cab be generated using the MPD for rescue operations, as mentioned below.

- Population Density Diagram: Metrics showing the density of the MPD populace in each square image pixel.
- Displacement Diagram: Metrics identified with MPD populace displacement between image pixels- sets.
- Well-being Check Diagram: Metrics showing the populace density of Safety Check registration nearby relief camps versus all solicitations for each image pixel.
- Battery charging Check Diagram: collects aggregate and smooth data on the count of cell-phones associating or disengaging from electricity.

6.4.5 Creation of data models in Deep learning for object detection on Aerial Imaging:

In disconnected architecture in flood environments, it is assumed that all the network connectivity has been lost through which a flood victim can communicate with the outer world in flood-affected areas. It is assumed that floods victims are looking for help in flood-affected areas that are not approachable in general context, and Rescue agencies have started their search and rescue operations. In this context, a drone will take a pre-defined route flight with high-resolution thermal cameras in the flood-affected area. It is assumed that rescue agencies have got some location inputs of the flood crisis area. To know the actual condition of that particular area,

this drone will fly on the pre-guided path and return with live high-resolution images and videos. These images and videos will be processed dynamically to perform search and rescue operations in the affected area immediately. When the drone flies in the air, it faces so many practical problems in collecting data and images for search and rescue operations in flood.

In the present approach, a superior system will be designed and implemented by developing techniques for

1. Reducing the fish-eye effect of drone images through analyzing various camera resolutions, field-view covered by the camera lens, size of the object, and drone distance between target and human.

2. Generating drone thermal maps through aerial geo-thermal infrared cameras and put in 'Deep learning' algorithms to identity humans in flood search and rescue operations. The work is certainly going to support rescue agencies to search individuals even in the complete night time in various unfavorable ecological conditions like total darkness, blinded by the front sunlight in the day time, ability to penetrate partial vegetation, and ability to see in different types of fog.

3. Creating models to search human patterns in images and video, especially in flood scenarios. TensorFlow object detection platform and Single Shot Detector (SSD) algorithm will be used. Aerial thermal images having tiny human patterns will be annotated for creating a test dataset for the small human object detection system.

The designed system will be tested with aerial thermal images having small human patterns inside structures.

6.4.6 Integration of techniques and the development of DSS for flood rescue operations:

In our proposed architecture, Social media is utilized to extract the meaningful information in the form of 'location events.' Location event is a geo-coordinate(x, y) along with the supporting contents where a flood crisis has been reported through social media or by any other means. A GIS-based system approach is proposed where the location events are visualized on the map. This map can contain additional relevant layers to perform spatial analytics. Mobile positioning Data of flood-affected areas are utilized from mobile network operators before the flood and during the flood to locate the people in flood-affected areas on live mode. The current live aerial images and videos through drones are obtained from that particular area and then searched the live human patterns in that particular area that are stuck and waiting for help in search and rescue operations in flood disasters.

From past research, it is observed that individual technologies and algorithms are selected. There is no linkage to create a system where different initiatives can talk to each other and provide an enterprise system. In our case, too, all the three data sources (Social media, Mobile Positioning Data, and Aerial Imaging), associated technologies, and applications mentioned in previous chapters will work independently. This study explains the linkage between all the three generated data and concepts to create an enterprise decision management system.

Twitter data creates a location event that is the first level of information. It is challenging to get all the important and required information to send a rescue team to search for humans accurately.

MPD data gets generated and analyzed with a census of flood-affected areas. It is observed that live coordinates could be traced to missing people. Rescue agencies wanted to know a GIS-based system where they can trace the missing people. Also, it is still unclear that what would be the next steps in case networks are down of that particular affected area.

In the aerial imagery techniques, the system collects aerial imagery in the shape of pictures and recordings. The study will collect live expected human patterns in flood-affected areas in the form of videos and images, but it is unclear that which team has to send and exactly where? Whether to send the NDRF Air-Force team, naval unit, or Army to rescue them. All these

potential questions will be solved if the different data sources could get integrated, and then a GIS-based enterprise DSS would be developed for search and rescue operations.

CHAPTER 8: REFERENCES

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